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Does income inequality facilitate carbon emission reduction in the US?

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ABSTRCT

Considering the short- and long-term impacts of income inequality on carbon emissions, as well as the heterogeneity of the emission distribution, this paper employs panel ARDL and quantile regression models to analyze the effect of income inequality on carbon emissions across US states. The findings suggest that higher income inequality increases US carbon emissions in the short term, whereas it promotes carbon reduction in the long term. Furthermore, we find that the absolute values for the coefficients on income inequality in the states from the 70th to the 90th quantiles are larger than those from the 10th to the 40th quantiles. This indicates that income inequality reduces more carbon emissions in states with higher per capita carbon emissions. The results provide important insights for policy makers to improve the quality of economic development and address climate change.

1. Introduction

Income inequality and environmental degradation have become salient political issues worldwide. As the largest economy and second largest carbon emitter in the world, the US shows prominent income inequality and faces heavy emission reduction pressure. BP data show that US carbon emissions still account for 15.2% of the worldwide carbon emissions although it has fell since 2016. The World Income Database further shows that the income share of the top 10% in the US increased from 43.9% in 2000 to 47% in 2014, and a growth trend is still observed.[1] This indicates that the proportion of wealth held by the rich is growing and income inequality is thus widening. The rapid economic growth is accompanied by income inequality expansion and environmental degradation (Kuznets, 1955; Fodha and Zaghdoud, 2010). Scholars claim that income inequality may increase the risk of social tensions, promote poverty-driven emigration, and degrade environmental quality (Hübler, 2017). Therefore, countries the world over pursue an inclusive development path of ecological civilization and reasonable income distribution. Clarifying the relationship between income inequality and carbon emissions can provide reference for achieving sustainable development and improving income allocation mechanism.

As the income inequality affects residents' consumption habits and manufacturers' production, which may takes a certain time to have impacts on energy structure and pollution emissions. Thus, the relationship between income inequality and carbon emissions may change over time. Meanwhile, the level of carbon emissions varies across regions. It can reveal the impacts of various parts of the entire carbon emission distribution when examine the relationship between income inequality and carbon emissions considering individual heterogeneity. Therefore, some questions naturally rise: (i) does income inequality affect US carbon emissions; (ii) are there different impacts of income inequality on US carbon emissions between the short- and long-term; and (iii) does income inequality have varied impacts under different carbon emission distributions? In any case, reducing carbon emissions and other greenhouse gas emissions is essential for preventing dangerous levels of climate change (Matsumoto et al., 2018). Therefore, addressing these questions can help us re-examine the effect of income inequality on carbon emissions and provide important references for policy makers.

Recently, scholars turned their attention to the income inequality and environmental pollution. Specifically, some studies support that income inequality has bad effect on environmental quality and propose that inequality leads to the increased

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[1] https://wid.world/country/usa/.

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consumption of carbon-intensive products (e.g., Grunewald et al., 2012; Golley and Meng, 2012; Baek and Gweisah, 2013; Zhang and Zhao, 2014; Jorgenson et al., 2017). Another viewpoint in literature is that income inequality could improve environmental quality. That is, when the income distribution is more balanced, the poor enter the middle class and consume more carbon-intensive products (e.g., Heerink et al., 2001; Borghesi, 2006; Jun et al., 2011; Grunewald et al., 2017; Hübler, 2017; Charfeddine and Mrabet, 2017). Recently, Jorgenson et al. (2017) used fixed and random effect models to analyze the effects of income inequality on carbon emissions across US states. However, their study did not analyze in depth the short- and long-term impacts, as well as the various impacts under different carbon emission distributions.

Using panel data on 51 states in US from 1997 to 2015, this paper first employs the fully modified ordinary least squares (FMOLS) and dynamic ordinary least squares (DOLS) models to analyze the long-term effects of income inequality on per capita carbon emissions. Then, we use a panel autoregressive distributed lag (ARDL) model to compare the short- and long-term effects of income inequality on carbon emissions. Considering distribution heterogeneity, we then conduct panel quantile regression to analyze various effects under different carbon emission distributions.

Our study contributes to the existing literature under three aspects. First, different from most studies focused on the national level, which may overlook heterogeneity (e.g., Hübler, 2017; Grunewald et al., 2017), we investigate the impact of income inequality on carbon emissions by using US state-level data. Additionally, by employing panel cointegration regression models (FMOLS and DOLS), this paper is the first, to the best of our knowledge, to investigate the long-term impact of income inequality on carbon emissions across US states. The FMOLS and DOLS models can non-parametrically correct ordinary least squares (OLS) estimations and eliminate the influence of noise parameters on the gradual distribution of statistics. They are thus suitable for analyzing long-term stability relationships.

Second, our study is the first to empirical analyze and compare the short- and long-term impacts of income inequality on carbon emissions across US states by using a panel ARDL model. The model is in fact a cointegration analysis of panel data, which can effectively estimate short- and long-term dynamic relationships. Since the model considers the lag of variables, the decomposition of model residuals can effectively reduce the endogeneity problem, making the conclusion more reliable. Different from Jorgenson et al. (2017) study, we find that income inequality increases carbon emissions in the short term, whereas it reduces carbon emissions and helps improve environmental quality in the long term.

Finally, we use the non-additive fixed effect panel quantile model, recently proposed by Powell (2016), to investigate the impact of US income inequality on carbon emissions under different carbon emission distributions. This model improves the traditional mean regression, fully considering the characteristic distribution of environmental variables. From the policy perspective, it is more interesting to find different impacts under extreme distributions. Under the framework of the panel quantile model, we find that income inequality contributes more to improve environmental quality in states with higher carbon emission distributions.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 introduces the models and data. Section 4 presents the empirical results. Section 5 is the conclusions and policy suggestions.

2. Literature review

Numerous studies have analyzed the effects of economic growth on environmental pollution, but no consensus has been hitherto reached on this topic. Grossman and Krueger (1991) proposed the environmental kuznets curve (EKC) hypothesis that economic growth would lead to increased pollution. However, once crossing a threshold point, the increase in income would contribute to environmental improvement. Many scholars have conducted empirical research to verify this hypothesis (e.g., Fodha and Zaghdoud, 2010; Saboori et al., 2012; Apergis and Ozturk, 2015; Dong et al., 2018; Xu et al., 2018). Their empirical analyses support the EKC hypothesis and show an inverted U-shaped impact of income on carbon emissions. However, some scholars consider that the EKC hypothesis does not exist (e.g., Perman and Stern, 2003; Lantz and Feng, 2006; Akbostancı et al., 2009; Diao et al., 2009; Nasir and Rehman, 2011; Onafowora and Owoye, 2014). In this respect, Xu (2018) argued that aggregate bias might lead to an erroneous estimation of the EKC hypothesis, and his study did not support the EKC hypothesis by using China's economic growth and SO_2 emissions data.

The existing research on economic growth and environmental pollution ignored an important factor that may affect environment quality: the polarization between the rich and the poor. As an extension of the EKC hypothesis, the effect of income inequality on environmental quality has gradually attracted scholarly attention. However, some scholars indicate that income inequality increases environment pollution. For instance, Grunewald et al. (2012) found that the higher household wealth, the more disproportionate is the increase in the demand for emissions-intensive products and services. Golley and Meng (2012) employed Chinese survey data to analyze changes in the carbon emissions of households at different income levels, and found that wealthy households spent more on and had higher energy consumption. It is generally considered that the per capita carbon emissions of the rich are higher than those of the poor. For example, Baek and Gweisah (2013) used US time series data and an ARDL model to analyze the relationship between income inequality and the environment. They found that fairer income distribution could improve environmental quality over both the short and long term. Zhang and Zhao (2014) proposed that a fairer income distribution has helped control China's CO_2 emissions. A win-win situation can be reached in income redistribution and emission reduction. These scholars proposed that narrowing income inequality and reducing carbon emissions could be achieved simultaneously.

Conversely, some scholars find that income inequality can improve environmental quality. For instance, Heerink et al. (2001) found that higher income inequality reduced carbon emissions significantly across countries. Borghesi (2006) measured income inequality by the Gini coefficient and, then, empirically analyzed the effect of income inequality on per capita carbon emissions in 35 countries, finding that, for poor countries, income inequality could effectively reduce pollution emissions. Jun et al. (2011) found that income inequality had a negative impact on pollution emissions and human capital progress could offset the adverse effects of income distribution differences. Grunewald et al. (2017) found that the effect of income inequality on carbon emissions depends on the income level. For low- and middle-income economies, the higher the income inequality, the lower the carbon emissions are. As such, income inequality could improve environmental quality. Hübler (2017) indicated that pollution emissions from household consumption increased in a concave relationship. Using quantile regression, he found that increased income inequality could reduce pollution emissions.

However, scholars still have not reached consensus on the effect of income inequality on carbon emissions, as extant studies mostly analyze the static effects, without considering their long-term relationship (e.g., Golley and Meng, 2012; Grunewald et al., 2017; Mader, 2018). Some researchers have focused on cointegration

analysis from the national perspective, revealing the long-term impact of income inequality on carbon emissions (e.g., Akbostancı et al., 2009; Baek and Gweisah, 2013; Onafowora and Owoye, 2014). Unfortunately, short- and long-term impacts within the same country have not been yet compared. Meanwhile, due to distribution heterogeneity, Hübler (2017) and Zhu et al. (2018) examined the effects of income inequality on carbon emissions under different carbon emissions quantiles. However, they focused on the various impacts across countries but not across US states. As such, the recent work by Jorgenson et al. (2017) is the closest to the scope of our study. They used the top 10% income ratio and the Gini coefficient to measure income inequality. Further, using fixed and random effect models, they found that income share of the top 10% was positively correlated with carbon emissions, and the Gini coefficient did not show significant effects. However, their study did not examine the short- and long-term effects of income inequality on carbon emissions across US states and they did not analyze the effects under different carbon emission distributions either.

Despite a large body of literature discuss income inequality and carbon emissions, there are still no studies that analyze the short- and long-term effects of income inequality on carbon emissions across US states, as well as considering carbon emission distributions. Therefore, we complement the study of Jorgenson et al. (2017) by using the FMOLS and DOLS models and conduct cointegration analysis to study the long-term effects of income inequality on per capita carbon emissions. We also employ a panel ARDL model to compare short- and long-term impacts. Furthermore, a panel quantile model is employed to investigate the various impacts under different carbon emission distributions. This approach will provide an important reference for US and other policymakers to understand income inequality and carbon emissions, to improve economic development quality and address climate change.

3. Models and data

3.1. Panel ARDL model

To examine the short- and long-term relationship between income inequality and CO_2 emissions, the panel ARDL approach introduced by Pesaran et al. (1999) is used in this paper. The panel ARDL model allows for the identification of short- and long-term relationships and can be categorized as an error correction model. The ARDL (p, q, q, …, q) model is expressed as follows:

$$\ln(CO_2)_{it} = \sum_{j=1}^{p} \lambda_{i,j} \ln(CO_2)_{i,t-j} + \sum_{j=0}^{q} \delta_{i,j}\mathbf{X}'_{i,t-j} + \gamma_i + \varepsilon_{i,t}. \tag{1}$$

Eq. (1) can be transformed into the following model:

$$\varDelta \ln(CO_2)_{i,t} = \varphi_i\left(\ln(CO_2)_{i,t-j} - \theta_{0,i} - \boldsymbol{\theta}_i\mathbf{X}_{i,t}'\right)\sum_{j=1}^{p-1} \lambda_{i,j}{}^{*} \varDelta \ln(CO_2)_{i,t-j} + \sum_{j=0}^{q-1} \delta_{i,j}{}^{*} \varDelta \mathbf{X}_{i,t-j}{}' + \eta_i + \varsigma_{i,t}, \tag{2}$$

where $\mathbf{X}_{i,t} = (\ln(P10_{i,t}), \ln(pgdp_{i,t}), (\ln(pgdp_{i,t}))^2, \ln(EC_{i,t}), \ln(Ind_{i,t}))$, CO_2 denotes the per capita CO_2 emissions, $P10$ denotes the income share of the top 10% as the proxy of income inequality, $pgdp$ denotes the per capita GDP, EC presents the per capita energy consumption, Ind is the industry structure, $\boldsymbol{\theta}_i$ measures the long-run impact of the explanatory variables on CO_2 emissions, and φ_i is the error corrector mechanism impact. $\gamma_i(\eta_i)$ is the group effect and $\varepsilon_{i,t}(\zeta_{i,t})$ is the error term and the remaining parameters are the short-run coefficients. We estimate Eq. (2) by employing the dynamic fixed effects (DFE) and the pooled mean group (PMG) estimators. The DFE estimator assumes the homogeneity of all parameters, except for the intercepts, across the sections in the panel. If the underlying model fails to meet these requirements, the DFE estimator is likely inconsistent. The PMG estimator allows the short-run parameters to vary from by states but forces the long-term ones to be homogenous.

3.2. Panel quantiles model

To investigate the heterogeneity effects of income inequality under different CO_2 emission distributions, a panel quantile regression model with the non-additive fixed effects proposed by Powell (2016) is used in this paper. It is appropriate to use quantile regression for empirical analysis if the variables have varying impacts at the different quantiles of the independent variable. As a result, a growing body of literature has combined quantile estimates with panel data. To capture within-group variation, the fixed effects are to be included in mean panel regression. Several scholars employed an analogous method to estimate quantile panel data, which considers additive fixed effects. However, the additive fixed effects change based on the model used. Therefore, according to Powell (2016), we use the non-additive fixed effects quantile regression for panel data (QRPD).

Compared with the traditional fixed effects quantile model that provides $\ln(CO_2)_{it} - \alpha_i$ givenD_{it}, the non-additive fixed effects quantile model provides an estimation of the distribution of $\ln(CO_2)_{it}$ given D_{it}. D_{it} represents the explanation variables. Powell (2016) noted that the observations at the top of the $(\ln(CO_2)_{it} - \alpha_i)$ distribution might be at the bottom of the $\ln(CO_2)_{it}$distribution. Therefore, Powell (2016) pointed out that the estimation could be expressed similar to the cross-sectional regression. The model can be written as follows:

$$\ln(CO_2)_{i,t} = \sum_{j=1}^{5} D'_{it}\beta_j\left(U^{*}_{it}\right), \tag{3}$$

where $\ln(CO_2)_{i,t}$ is the per capita CO_2 emission for state i at year t, and β_{it} is the parameter of interest. Except for income inequality, we set the following control variables: per capita GDP and its quadratic term (Martínez-Zarzoso and Maruotti, 2011), per capita energy consumption (Shuai et al., 2011) and industry structure (Xie et al. 2017, 2018). U^{*}_{it} is the error term. The model is linear in parameters and $D'_{it}\beta(\tau)$ is strictly increasing in τ. For the τ^{th} quantile of $\ln(CO_2)_{i,t}$, the quantile regression relies on the following conditional restriction:

$$P\left(\ln(CO_2)_{i,t} \le D'_{it}\beta(\tau)|D_{it}\right) = \tau. \tag{4}$$

Eq. (4) indicates the probability of the dependent variable. The QRPD estimation allows for the probability to vary by individual and even within-individual if the variation is orthogonal to the instruments. Therefore, QRPD relies on a conditional and an

unconditional restriction, setting $D_i = (D_{it}, \cdots, D_{iT})$:

$$P\left(\ln(CO_2)_{i,t} \le D'_{it}\beta(\tau) | D_{i,t}\right) = P\left(\ln(CO_2)_{i,t} \le D'_{i,s}\beta(\tau) | D_{i,t}\right),$$

$$P\left(\ln(CO_2)_{i,t} \le D'_{i,t}\beta(\tau)\right) = \tau \tag{5}$$

Powell (2016) also proposed the estimation in the instrumental variables context given instruments $Z_{it} = (Z_{i1}, \cdots, Z_{iT})$. However, if the explanatory variables were exogenous such as $D_i = Z_i$, some identification conditions were met trivially. Therefore, we use the generalized method of moments for the estimates. Sample moments can be expressed as follows:

$$\widehat{g}(b) = \frac{1}{N}\sum_{i=1}^{N} g_i(b) \text{ with } g_i(b) = \frac{1}{T}\left\{\sum_{i=1}^{T}(Z_{it} - \overline{Z}_i)\left[1\left(\ln(CO_2)_{i,t} \le D'_{i,t}b\right)\right]\right\} \tag{6}$$

where $\overline{Z}_i = \frac{1}{T}\sum_{i=1}^{T} Z_{it}$.

Using Eq. (6), the parameter set can be expressed as:$B \equiv \left\{ b | \tau - \frac{1}{N} \le \frac{1}{N}\sum_{t=1}^{N}(\ln(CO_2)_{i,t} \le D'_{i,t}b) \le \tau \right\}$ for all t. The parameter can then be estimated as $\widehat{\beta}(\tau) = \underset{b \in \beta}{\operatorname{argmin}}\,\widehat{g}(b)\widehat{A}\widehat{g}(b)$ with weighting matrix $\widehat{A}$. The model is estimated using the Markov Chain Monte Carlo optimization method.

3.3. Data

This study mainly addresses how income inequality affects carbon emissions in US. Previous literature on this subject mostly adopts time series data and relatively less concerned about the heterogeneity of carbon emissions across US states. For an in-depth analysis, we choose 50 US states and the District of Columbia as our sample in 1997–2015. This study uses 969 observations.

Following Jorgenson et al. (2017), the income share of the top 10% is used as the proxy of income inequality ($P10$). The data of income share of the top 10% is collected from the World Wealth and Income Database, developed by Frank and Mark (2009). These data are measured in percentages. For the dependent variable, unlike Jorgenson et al. (2017) who set the carbon emissions in state level as the proxy of environmental quality, we set per capita carbon emissions as a proxy that covers economy-wide emissions.

The data on per capita energy consumption (EC) and per capita carbon emissions (CO_2) are obtained from the US Energy Information Administration (EIA).[2] The industry structure (Ind) is estimated by the ratio of the manufacturing output to GDP. The data on per capita GDP ($pgdp$) (reported in constant 2007 USD) and manufacturing data are obtained from the Bureau of Economic Analysis database[3] released by United States Department of Commerce.

The statistical descriptions of variables are shown in Table 1. All variables are expressed as natural logarithms. The Jarque-Bera (JB) test confirms the rejection of the null hypothesis that all series are normal description at the 1% significance level. Meanwhile, the skewness and kurtosis indicate that the distribution of the sample data is not normal. These results reveal that the linear regression model based on the conditional mean estimation may encounter challenges (Zhu et al., 2015). This leads us to employ the quantile regression approach to determine whether the effect of income inequality on carbon emissions is heterogeneous across states based on their carbon emission levels. Fig. 1 shows a scatter plot of the association between carbon emissions per capita the income inequality. We find that the carbon emissions per capita are negatively associated with income inequality based on data of US states.

Table 1
Statistics description.

	ln CO_2	ln $P10$	ln EC	ln $pgdp$	ln Ind
Mean	−4.698	1.641	7.464	4.657	1.038
Median	−4.722	1.636	7.487	4.642	1.109
Maximum	−3.886	1.794	9.034	5.232	1.487
Minimum	−5.372	1.518	4.865	4.451	−0.693
Std. Dev.	0.247	0.049	0.749	0.111	0.318
Skewness	0.822	0.425	−0.543	2.181	−2.499
Kurtosis	4.181	3.403	3.925	11.685	12.106
Jarque-Bera	165.548***	35.759***	82.213***	3813.861***	4356.288***
Obs.	969	969	969	969	969

Notes: *, **, *** are statistical significance at 10%, 5% and 1%, respectively.

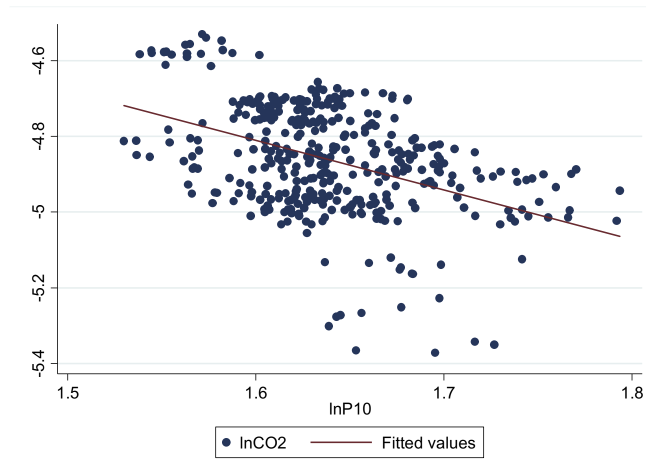

Fig. 1. Scatter plot: per capita carbon emissions and income inequality
Notes: ln CO_2 denotes the per capita carbon emissions; ln $P10$ represents the income share of the top 10% measured as the income inequality.

4. Empirical results

4.1. Panel causality test

We test whether the variables are stationary before estimating the panel regression model. The unit root test results are shown in Table A1. It indicates that all variables are integrated of order one, I (1). Given that all variables are stationary after the first-order difference, we use panel cointegration test to examine whether there exists a long-term equilibrium relationship between carbon emissions and their driving factors. The results are presented in Table A2. There is strong statistical evidence in favor of panel cointegration among variables.

In this section, two panel Granger causality tests are used to examine the causal relationship among carbon emissions and their possible impact factors. The first panel Granger causality test considers the panel data as a large stacked dataset and runs the standard Granger causality test. This approach assumes that all coefficients are the same on all cross sections, but do not allows for data from one cross-section to enter the lagged values of data from

[2] https://www.eia.gov/state/seds/seds-data-complete.php?sid=US#Production.
[3] http://www.bea.gov/index.htm.

Table 2
Panel causality test.

Panel 1: Panel causality test: stacked test	
Null Hypothesis:	F-Statistic
ln *P10* does not cause $\ln(CO_2)$	7.812***
ln *pgdp* does not Granger Cause $ln(CO_2)$	11.771***
ln *EC* does not Granger Cause $\ln(CO_2)$	1.026
ln *Ind* does not Granger Cause $\ln(CO_2)$	3.822**
Panel 2: Panel Causality Test: pairwise Dumitrescu Hurlin (2012) test	Zbar-Stat.
Null Hypothesis:	
ln *P10* does not homogeneously cause $\ln(CO_2)$	2.998***
ln *pgdp* does not homogeneously cause $\ln(CO_2)$	4.984***
ln *EC* does not homogeneously cause $\ln(CO_2)$	4.341***
ln *Ind* does not homogeneously cause $\ln(CO_2)$	2.714***

Notes: *, **, *** are statistical significance at 10%, 5% and 1%, respectively.

the subsequent cross-section. The second method is proposed by Dumitrescu-Hurlin (2012), which allows all coefficients to vary across cross-sections. The panel Granger causality test results are presented in Table 2. According to the first approach, we find causality from the factors of income inequality, per capita GDP and industry structure to carbon emissions, except for energy consumption per capita. However, under the framework of Dumitrescu-Hurlin (2012), considering the dependence among states and heterogeneity, we find the test rejects the null hypothesis of no homogeneous causality for all impact factors. These factors thus have a significant impact on carbon emissions.

4.2. Cointegration regression

In the previous section, we have identified a long-term cointegration relationship between carbon emissions and their influencing factors. This section further investigates the long-term parameters of the relationship between the carbon emissions and the other variables, that is, how income inequality affects the carbon emissions in the long term. For this purpose, we use two cointegration regression models — panel FMOLS and DOLS, developed by Pedroni (2001, 2002). The results are shown in Table 3.

As per column (1) of Table 3, the coefficient of ln *P10* with respect to carbon emission is negative and statistically significant at the 1% level. This reveals that income inequality has negative impacts on carbon emissions per capita in the long term. For adding control variables gradually, the results are shown in columns (2)–(4) of Table 3, being stable and the income inequality having negative impacts on the carbon emissions. This finding is consistent with Hübler (2017), who used cross-country data to identify that increases in income inequality represented by the Gini index could reduce carbon emissions per capita. Hübler (2017) also proposed that households' contributions to an economy's emissions were concave in household income. That is, a household's emissions increase less than proportionally when the household's income rises. As inequality increases, economy-wide (per capita) emissions will thus decrease. Our findings are different from those of Jorgenson et al. (2017), who supported that US state-level emissions are positively associated with the income share of the top 10% by using OLS estimations. Different empirical data and methods may have caused the different results. In terms of estimation methods, we consider long-term effects by using the FMOLS and DOLS models. These two models can non-parametrically correct the OLS estimation and eliminate the influence of noise parameters on the gradual distribution of statistics, being more robust than OLS regression.

Additionally, we find energy consumption to be positively associated with carbon emissions. The coefficients on ln *pgdp* and its quadratic term are positive and negative, respectively. This confirms the existence of the EKC hypothesis in the long term. Furthermore, the development of manufacturing has a significant positive impact on carbon emissions. Under the DOLS model framework, we find similar conclusions with those of the FMOLS model. In sum, we provide evidence that long-term income inequality has significant negative impacts on carbon emissions.

4.3. Panel ARDL regression analysis

As discussed in Subsection 4.2, income inequality has a negative impact on carbon emissions in long term under the frameworks of the FMOLS and DOLS models. To further test the different impacts

Table 3
Results of cointegration regression.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FMOLS	FMOLS	FMOLS	FMOLS	DOLS	DOLS	DOLS	DOLS
	−0.981***	−0.867***	−0.572***	−0.482***	−0.974***	−0.848***	−0.665***	−0.597***
	(-10.285)	(-11.606)	(-7.888)	(-6.895)	(-7.810)	(-8.416)	(-8.269)	(-7.272)
		0.409***	0.488***	0.457***		0.468***	0.547***	0.548***
		(14.296)	(18.491)	(17.681)		(13.653)	(18.013)	(17.904)
			10.140***	8.412***			11.965***	10.601***
			(4.422)	(3.785)			(3.831)	(3.492)
			−1.140***	−0.941***			−1.313***	−1.163***
			(-4.657)	(-3.963)			(-3.930)	(-3.582)
				0.141***				0.125***
				(5.737)				(4.475)
R^2	0.969	0.980	0.984	0.986	0.975	0.988	0.991	0.992

Notes: t statistics in parentheses. *, **, *** are statistical significance at 10%, 5% and 1%, respectively.

Table 4
Results of panel ARDL regression.

		(1) PMG	(2) DFE
Long-run Coefficients	ln *P10*	−0.292***	−0.689***
		(-4.920)	(-3.820)
		0.377***	0.486***
		(18.760)	(8.140)
		7.255***	8.468*
		(3.690)	(1.730)
		−0.828***	−0.973*
		(-3.940)	(-1.860)
		0.151***	0.144**
		(7.420)	(2.520)
Error Correction Coefficients	ECT (−1)	−0.237***	−0.162***
		(-5.910)	(-8.850)
Short-run Coefficients	Δln *P10*	0.004	0.066**
		(0.100)	(2.210)
		0.288***	0.277***
		(8.660)	(15.870)
		−15.712	−0.794
		(-1.480)	(-0.370)
		1.710	0.107
		(1.480)	(0.470)
		−0.043	−0.023
		(-1.420)	(-1.380)
	Constant	−5.442***	−4.167**
		(-5.890)	(-2.190)
Hausman test	X2 (Prob)		
	H_0: PMG v.s. DFE	0.000 (1.000)	
	N	969	969

Notes: t statistics in parentheses. H_0: The DFE estimator is preferred than PMG estimator. *, **, *** are statistical significance at 10%, 5% and 1%, respectively.

of income inequality on carbon emissions in the short and long term, a panel ARDL model is employed. Table 4 reports the results obtained from the panel ARDL model based on the PMG and DFE estimators. For the panel ARDL analysis, the Hausman test implies a choice between the PMG and DFE estimators, and the null hypothesis of the Hausman test is that DFE estimators are preferred over PMG estimators (i.e., slope parameters remain constant across states). Because the null hypothesis cannot be rejected, the DFE is the appropriate estimator for the model. As per column (2) of Table 4, according to the DFE estimates, we find the error correction term to be negative and significant, which proves that the process converges over the long term.

Regarding income inequality, we find the coefficient on income inequality (ln *P10*) to be negative and statistically significant in the long term, indicating that an increase in income inequality can help reduce carbon emissions per capita. However, in the short term, the estimated coefficient on Δln *P10* is positive and significant at the 5% level. This indicates that carbon emissions are positively associated with income inequality in the short term across US states, whereas it facilitates carbon mitigation in the long term. The reasons behind these findings may be that people with high income carry on more life activities for getting larger utility, which leads the increase of carbon emissions. However, based on the law of diminishing marginal utility, the rich has smaller marginal utility of money than the poor do. Therefore, in the long term, the rich will product less carbon emission from life consumption due to their limited marginal utility of money; meanwhile, the poor also product less carbon emission due to limited consumption ability that caused by the income moving from poor to the rich. Our results are different from Jorgenson et al. (2017) who used the fixed and random effect models and found that the top 10% income was positively correlated with carbon emissions across US states. The reasons behind the differences may be that their study did not identify the short- and long-term effects of income inequality on carbon emissions across US states under the framework of panel ARDL model. Besides, regarding to data and variables, compare to Jorgenson et al. (2017) we refresh the data to 2015 in this paper. In addition, unlike Jorgenson et al. (2017) who use the total carbon emission as the proxy of environment quality, we select the per capita carbon emission that has more comprehensive representative.

For the control variables, we find that energy consumption per capita has a significant positive impact on carbon emissions both in the short and long term. Concerning variable ln *pgdp*, the EKC hypothesis is valid in the long term. However, in the short term, the coefficients on ln *pgdp* and its quadratic term are insignificant. This reveals that the EKC hypothesis does not exist in the short term across US states. Regarding industry structure, this shows that the coefficient on ln *Ind* is positive and significant at the 1% level, providing evidence that, in the long term, an increase in the manufacturing output could lead to an increase in carbon emissions. However, the coefficient on Δln *Ind* is insignificant, indicating the increase in manufacturing does not have a direct effect on the environment in the short term.

4.4. Panel quantiles regression results

To investigate whether the impact of income inequality on carbon emissions is heterogeneous across states based on their carbon emission levels, we apply a panel quantile regression proposed by Powell (2016). By the quantile regression, the entire conditional distribution of the dependent variable (per capita carbon emissions) can be described. Utilizing this model can estimate the impact of income inequality on carbon emissions under the conditional distribution, with special focus on the most and least polluting states. The results of the conditional emission distributions are reported in Table 5.

We find the response of per capita carbon emission to income inequality to be clearly heterogeneous across different quantiles, but it still supports that higher income inequality decreases carbon emissions. That is, the impacts vary under different carbon emission distributions. Specifically, at the 10th, 20th, and 30th low quantiles, which correspond to the lower carbon emission states, the estimated coefficients on ln *P10* are −0.527, −1.376, and −0.732

Table 5
Results of panel quantile regression.

	10th	20th	30th	40th	50th	60th	70th	80th	90th
	−0.527***	−1.376***	−0.732***	−1.571***	−1.341***	−2.195***	−2.270***	−2.233***	−1.584**
	(-25.40)	(-352.24)	(-13.05)	(-53.31)	(-119.01)	(-110.75)	(-136.19)	(-181.26)	(-52.97)
	0.028***	0.076***	0.083***	0.086***	0.057***	0.099***	0.075***	0.098***	0.055*
	(21.66)	(141.12)	(6.85)	(65.280)	(79.440)	(41.390)	(35.480)	(61.760)	(2.160)
	9.506***	3.433***	39.47***	12.74***	4.580***	10.27***	12.47***	8.947***	26.91***
	(21.800)	(6.580)	(14.090)	(14.000)	(81.650)	(19.380)	(43.590)	(38.860)	(5.570)
	−1.033***	−0.396***	−4.198***	−1.415***	−0.569***	−1.127***	−1.350***	−1.017***	−2.966***
	(-23.17)	(-7.30)	(-14.29)	(-14.26)	(-90.43)	(-20.07)	(-49.63)	(-43.76)	(-5.90)
	0.022***	0.122***	0.059***	−0.038***	−0.095***	−0.114***	−0.0771***	−0.127***	−0.458***
	(6.500)	(17.200)	(5.590)	(-7.72)	(-65.67)	(-23.97)	(-7.64)	(-29.41)	(-9.34)
N	969	969	969	969	969	969	969	969	969

Notes: t statistics in parentheses. *, **, *** are statistical significance at 10%, 5% and 1%, respectively.

and significant at the 1% level, respectively. By contrast, at the 70th, 80th, and 90th high quantiles, which correspond to the higher CO_2 emission states, the coefficients on ln *P10* are −2.270, −2.233, and −1.584, respectively. This reveals that the income inequality has a greater reduction effect on carbon emissions in the states with higher carbon emissions than in those with lower carbon emissions. The result is consistent with Hübler (2017), who identified higher marginal emission savings in countries with high per capita emissions than that in less emissions countries.

Additionally, we find that energy consumption increases the carbon emissions, but there exist heterogeneous effects across different quantiles. For states with higher carbon emissions, energy consumption has a greater effect on carbon emissions than that in states with lower carbon emissions. Moreover, we find that the coefficient on ln *pgdp* is positive and its quadratic term coefficient is negative at each quantile. This proves the existence of the EKC hypothesis for US states under different carbon emissions levels. It is worth noting that industry structure shows significant heterogeneity in its impact on carbon emissions. Particularly, at the 10th and 20th low quantiles, we find the coefficients on ln *Ind* are significant and positive at the 10% level. However, at the higher quantiles, such as the 70th, 80th, and 90th, we find that the coefficients are negative and significant. This indicates that the expansion of manufacturing increases carbon emissions for states with lower carbon emissions, while it has a mitigation effect for states with higher carbon emissions.

5. Conclusions

Rapid economic growth is accompanied by an income gap expansion and environmental degradation. Recent years, numerous scholars are gradually paying attention to the role of income inequality in climate change. In this paper, we analyze the short- and long-term impacts of income inequality on carbon emissions across US states. Furthermore, considering distribution heterogeneity, we analyze the various effects under different carbon emission distributions by using a panel quantile model. The results provide important insights for policymakers to improve the quality of economic development and address the problems of climate change.

Using panel ARDL regression, we find that (i) income inequality increases carbon emissions in the short-term across US states, whereas it facilitates carbon emission reduction in the long-term. (ii) The cointegration regression results also confirm that increasing income inequality contributes to carbon emission mitigation in the long-term across US states. (iii) The panel quantile regression results show that the coefficients on income inequality for the states from the 70th to the 90th quantiles are larger than those from the 10th to the 40th quantiles. This reveals that income inequality has a much greater carbon emission reduction effect for some states with higher per capita carbon emission.

Based on the above results, we propose the following policy recommendations. First, the US government needs to pay more attention to the quality of economic development, while keeping the resident income growing steady. Moreover, it is necessary to establish a stable income growth mechanism for low- and middle −income residents when adjusting income distribution. Policymakers should ensure that income increases for the poor do not translate into higher emissions. As such, environment pressure can be reduced when distributing income more equitably. Second, regional differences for carbon emission should be considered in policy formulation and implementation. The purpose of policies should be established to improve the overall welfare of the society and narrow the differences in carbon emissions and economic development levels across regions. All the efforts should contribute to regional convergence. Regions with higher carbon emissions should invest more to guide the consumption of the poor and tackle environmental governance and income distribution. The government should appropriately increase the responsibilities of the rich in environmental protection and governance, such as collecting environmental taxes that are positively related to income levels. Lastly, promoting green lifestyle through policy guidance and improving residents' environmental awareness are the nice ways to reduce carbon emissions. The government should provide more green public goods and service. Advanced technologies can be thus introduced to guide residents to increase their demand for green products.

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Appendix A

We use the Fisher ADF unit root test (Maddala and Wu, 1999), Fisher PP unit root tests (Choi, 2001) and LLC unit root tests (Levin et al., 2002) to examine the stationary properties of variables. The three approaches test the null hypothesis that there is a unit root for the data. The test results are shown in Table A1. We find that the series of industry structure (ln *Ind*) is stationary and so is its first-order differenced series. Other variables are stationary series after a first-order difference at the 1% significance level for the sample data. This indicates that all variables are integrated of order one, I(1).

Table A1
Panel unit root tests.

	Level			First difference		
	LLC	ADF	PP	LLC	ADF	PP
ln CO_2	7.544	14.063	11.671	−20.049***	521.385***	830.184***
	(1.000)	(1.000)	(1.000)	(0.000)	(0.000)	(0.000)
ln *P10*	5.065	22.455	17.1932	−22.7843***	588.433***	943.333***
	(1.000)	(1.000)	(1.000)	(0.000)	(0.000)	(0.000)
ln *EC*	−1.080	65.341	97.572	−24.463***	652.327***	908.779***
	(0.140)	(0.998)	(0.606)	(0.000)	(0.000)	(0.000)
ln *pgdp*	8.492	11.295	6.157	−15.942***	382.296***	481.209***
	(1.000)	(1.000)	(1.000)	(0.000)	(0.000)	(0.000)
ln *Ind*	−8.24***	191.921***	286.891***	−17.699***	452.722	756.942***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: The significance probabilities for corresponding tests are reported in parentheses. *, **, *** are statistical significance at 10%, 5% and 1%, respectively.

Table A2
Panel cointegration test.

Hypothesized	Fisher Stat.*		Fisher Stat.*	
No. of CE(s)	(from trace test)	Prob.	(from max-eigen test)	Prob.
None	224***	0.000	224***	0.000
At most 1	786.1***	0.000	786.1***	0.000
At most 2	1553***	0.000	1054***	0.000
At most 3	738.9***	0.000	530.2***	0.000
At most 4	340.1***	0.000	284.9***	0.000
At most 5	214.8***	0.000	214.8***	0.000

Notes: *, **, *** are statistical significance at 10%, 5% and 1%, respectively.

Panel cointegration is checked by using the Johansen–Fisher test and the results are presented in Table A2. The Johansen–Fisher test indicates that there exist five cointegrating vectors at 5% significance level. Overall, there is strong statistical evidence in favor of panel cointegration among carbon emissions, income inequality, energy consumption, industry structure, PGDP, and its quadratic term.

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